Learning-by-exporting in Korean Manufacturing: A Plant-level Analysis

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Abstract

This study analyzes whether firms that start exporting become more productive using matched sampling techniques to control for the self-selection into export market. To do so, we use plant level panel data on Korean manufacturing sector in the period 1990-2006. We find clear and robust learning-by-export effect; the total factor productivity gap between exporters and their domestic counterparts arises and widens during several years after export market entry. We also find that the effect is more pronounced for firms that have higher skill-intensity, higher share of exports in production, and small in size. Overall, the evidence suggests that exporting is one important channel for domestic firms to acquire advanced foreign knowledge. Also, the stronger learning-by-doing effect for firms with higher skill-intensity seems to support the view that "absorptive capacity" matters to receive knowledge spillovers from exporting activity.

I. Introduction and Background

One of the most frequently asked question in trade and growth literature is whether and how international trade or openness of trading regime promotes productivity growth of countries. Although numerous studies, both theoretical and empirical, have been conducted on this issue, there seem to be no clear consensus yet on this issue. Recently, a growing number of studies utilized firm or plant level data and re-examined this issue, particularly focusing on exporting as a channel of international technology diffusion or knowledge spillovers. One empirical regularity emerging from these studies is that exporters are more productive than non-exporters. The positive cross-sectional correlation between exporting and productivity, however, might reflect causality in either direction, or both. On one hand, exporters could already be more productive than non-exporters before they started exporting (self-selection). On the other hand, exporters could gain new knowledge and expertise after entering the export market and improve their productivity relative to industry norms (learning-by-exporting). The self-selection hypothesis is supported by most studies, but the evidence on learning-by-exporting seems less clear-cut (Tybout 2000).[1]

This study uses matched sampling techniques and examines the exporting-productivity nexus using the plant level panel data on Korean manufacturing sector (Survey of Mining and Manufacturing, SMM henceforth) during the period from 1990-

[1] Previous studies on Korea include Aw, Chung, and Roberts (2000) and Hahn (2004). Aw, Chung, and Roberts could not find evidence in favor of either learning-by-exporting or self-selection in Korea. Although Hahn (2004) uses two methodologies by Bernard and Jensen (1999a, 1999b) and finds some evidence of both selection and learning, the results are not very robust.

2006. Main question to be addressed in this study is whether exporting activity improves productivity performance of plants. This paper's focus on learning-by-exporting stems from the recognition that this is where the empirical evidences of existing studies are most mixed and, nevertheless, whether learning-by-exporting effect exists or not has an important implication on the formulation of appropriate "openness" policies. As discussed by Bernard and Jensen (1999a), if gains do accrue to firms once they become exporters, then the appropriate policy interventions would be those that reduced barriers to entering foreign markets, which include macroeconomic trade policies designed to increase openness to trade and microeconomic policies to reduce entry costs, such as export assistance, information programs, joint marketing efforts, and trade credits. If there are no post-entry rewards from exporting, then policies designed to increase the numbers of exporters may be wasting resources.[2]

This study examines further some of the conditions under which the learning-by-exporting may or may not take place, utilizing information on various plant or industry characteristics. As plant characteristics, we consider skill-intensity, export propensity, plant size, and R&D intensity. Although most existing studies utilized information only on whether a plant exports or not, it is plausible that the degree of learning-by-exporting might be related to how much important exporting activity is to the plant involved, for example, in as much as learning-by-exporting arises through interactions with foreign buyers and these interactions require resources. Thus, we examine whether plants with higher export propensity exhibits stronger learning-by-exporting. Meanwhile, if knowledge spillovers from exporting activity require domestic "absorptive capacity", then we could expect that plants with higher absorptive capacity will exhibit stronger

[2] See Bernard and Jensen (1999a) for a detailed argument.

learning-by-exporting. We use skill-intensity of plants as a proxy for the domestic absorptive capacity.

As industry characteristics, we consider industry-level destination of exports. De Loecker (2007) shows that the degree of learning-by-exporting depends on destination of exports, using plant level information on export destination in Slovenian manufacturing. This analysis is based on the presumption that learning-by-exporting effect will be stronger for plants that start exporting to more advanced countries. In the case of Korea, however, plant level information on export destination is not available. So, we examine instead whether plants in industries with higher share of exports to advanced countries exhibit stronger learning-by-exporting.

There are some empirical studies that examine causal relationship between exporting and productivity. Most studies report that exporters are more productive than non-exporters before they start exporting, suggesting that cross-sectional correlation between exporting and productivity partly reflects a self-selection effect. For example, Clerides, Lach and Tybout (1998) find very little evidence that past exporting improves performance, using the plant-level panel data from Colombia, Mexico, and Morocco. Similar results are reported by Aw, Chung, and Roberts (2000) and Aw, Chen, and Roberts (2001) for Taiwan, Bernard and Jensen (1999b) for U.S. By contrast, the evidence on learning is mixed. On one hand, the above studies find little evidence in favor of learning. Although Bernard and Jensen (1999b) report that new entrants into the export market experience some productivity improvement at around the time of entry, they are skeptical about the existence of strong learning-by-exporting effect. On the other hand, several recent studies using matched sampling techniques—Girma, Greenaway, and Kneller (2004) for UK, De Loecker (2007) for Slovenia, Albornoz and

Ercolani (2007) for Argentina— provide empirical evidence in favor of learning-by-exporting.

Related previous studies on Korea include Aw, Chung, and Roberts (2000) and Hahn (2004). Aw, Chung, and Roberts (2000), using plant-level panel data on Korean manufacturing for three years spaced at five-year interval, supports neither self-selection nor learning-by-exporting in Korea. This study differs from studies on other countries in that even the self-selection hypothesis is not supported. They argue that Korean government's investment subsidies tied to exporting activity rendered plant productivity a less useful guide on the decision to export. By contrast, following the methodologies of Bernard and Jensen (1999a, 1999b), Hahn (2004) finds some evidence of both selection and learning, using annual plant-level panel data from 1990 to 1998. However, the methodologies used by Hahn (2004) did not control for the self-selection in export market participation, and the results were sensitive to methodologies.

In this paper, we use both propensity score matching and one-to-one matching to control for the self-selection in export market participation, and re-examine learning-by-exporting hypothesis in Korean manufacturing. We find clear and robust learning-by-export effect; the total factor productivity gap between exporters and their domestic counterparts arises and widens during several years after export market entry. We also find that the effect is more pronounced for firms that has higher skill-intensity and higher share of exports in production.

The organization of this paper is as follows. The following section explains the data and calculation of plant total factor productivity. Section 3 explains the methodology to estimate the effect of learning-by-exporting. Section 4 discusses our main empirical results. Final section concludes with remarks on issues that could be covered in the final report.

II. Data and Plant Total Factor Productivity

II. 1 Data

The data used in this study is the unpublished plant-level census data underlying the *Survey of Mining and Manufacturing*. The data covers all plants with five or more employees in 580 manufacturing industries at KSIC (Korean Standard Industrial Classification) five-digit level. It is an unbalanced panel data with about 69,000 to 97,000 plants for each year during the 1990-1998 period. For each year, the amount of exports as well as other variables related to production structure of plants, such as production, shipments, number of production and non-production workers, tangible fixed investments, are available. The exports in this data set include direct exports and shipments to other exporters and wholesalers, but do not include shipments for further manufacture.

II. 2 Plant Total Factor Productivity

Plant total factor productivity is estimated using the chained-multilateral index number approach as developed in Good (1985) and Good, Nadiri, and Sickles (1997). It uses a separate reference point for each cross-section of observations and then chain-links the reference points together over time. The reference point for a given time period is constructed as a hypothetical firm with input shares that equal the arithmetic mean input shares and input levels that equal the geometric mean of the inputs over all cross-section observations. Thus, the output, inputs, and productivity level of each firm in each year is measured relative to the hypothetical firm at the base time period. This approach allows us to make transitive comparisons of productivity levels among observations in a panel data set.[3]

Specifically, the productivity index for firm i at time t in our study is measured in the following way.

$$\ln TFP_{it} = (\ln Y_{it} - \overline{\ln Y_t}) + \sum_{\tau=2}^{t}(\overline{\ln Y_\tau} - \overline{\ln Y_{\tau-1}}) -$$

$$\left\{ \sum_{n=1}^{N}\frac{1}{2}(S_{nit} + \overline{S_{nt}})(\ln X_{nit} - \overline{\ln X_{nt}}) + \sum_{\tau=2}^{t}\sum_{n=1}^{N}\frac{1}{2}(\overline{S_{n\tau}} + \overline{S_{n\tau-1}})(\overline{\ln X_{n\tau}} - \overline{\ln X_{n\tau-1}}) \right\},$$

where Y, X, S, and TFP denote output, input, input share, TFP level, respectively, and symbols with upper bar are corresponding measures for hypothetical firms. The subscripts τ and n are indices for time and inputs, respectively. In our study, the year 1990 is the base time period.

As a measure of output, we used the gross output (production) of each plant in the Survey deflated by the producer price index at disaggregated level. As a measure of capital stock, we used the average of the beginning and end of the year book value capital stock in the Survey deflated by the capital goods deflator. As a measure of labor input, we used the number of workers, which includes paid employees (production and non-production workers), working proprietors and unpaid family workers. Here, we allowed for the quality differential between production workers and all the other types of workers. The labor quality index of the latter was calculated as the ratio of non-

[3] Good, Nadiri, and Sickles (1996) summarize the usefulness of chaining multilateral productivity indices succinctly. While the chaining approach of Tornqvist-Theil index, the discrete Divisia, is useful in time series applications, where input shares might change over time, it has severe limitations in cross-section or panel data where there is no obvious way of sequencing the observations. To the contrary, the hypothetical firm approach allows us to make transitive comparisons among cross-section data, while it has an undesirable property of sample dependency. The desirable properties of both chaining approach and the hypothetical firm approach can be incorporated into a single index by chained-multilateral index number approach.

production workers' and production workers' average wage of each plant, averaged again over the entire plants in a year. As a measure of intermediate input, we used the "major production cost" plus "other production cost" in the Survey. Major production cost covers costs arising from materials and parts, fuel, electricity, water, manufactured goods outsourced and maintenance. Other production cost covers outsourced services, such as advertising, transportation, communication and insurance. The estimated intermediate input was deflated by the intermediate input price index.

We assumed constant returns to scale so that the sum of factor elasticity equals to one. Labor and intermediate input elasticity for each plant are measured as average cost shares within the same plant-size class in the five-digit industry in a given year. Thus, factor elasticities of plants are allowed to vary across industries and size classes and over time. Here, plants are grouped into three size classes according to the number of employees: 5-50, 51-300, and over 300.

II. 3 Definition of Exporters

We start by defining exporters in a given year as plants which reported positive amount of exports, following convention in the literature. Accordingly, non-exporters in a given year are those plants with zero exports. With this definition of exporters, it is possible to classify all plants that appear in the data set in the period 1990-1998 into five sub-groups: always, never, starters, stoppers, and other.[4] "Always" is a group of plants that were exporters in the first year they appear in the dataset and never switched their exporting status. Similarly, "never" is a group of plants that were non-exporters in the

[4] We eliminated plants that switch in and out of the dataset more than twice during the period from 1990 to 1998. Thus, we keep only those plants that do not have a split in time series observations. This procedure eliminates about 10? percent of the sample in terms of number of plants.

first year they appear in the dataset and never switched their exporting status. “Starters” is a group of plants that were non-exporters in the first year they appear, switched to exporters, and remained as exporters thereafter. “Stoppers” is a group of plants that were exporters in the first year they appear, switched to non-exporters, and never switched back. All other plants, which switched their exporting status more than twice during the sample period, are grouped as “other”.

II. 4 A Preliminary Analysis: Performance of Exporters and Non-exporters

<Table 1> shows the number of exporting plants and average exports as percentage of shipments (export intensity) during the 1990-1998 period. During the sample period, the exporting plants accounted for between 11.0 and 15.3 percent of all manufacturing plants. The share of exporting plants rose slightly between 1990 and 1992, but since then it steadily declined until 1996. However, with the outbreak of the financial crisis in 1997, the share of exporting plants rose somewhat noticeably to reach 14.8 percent in 1998. The rise in the share of exporting plants since 1997 can be attributed mostly to the closing of non-exporting plants, rather than increase in the number of exporting plants. The increase in the number of exporters since 1997 was only modest. These changes are broadly consistent with the severe contraction of domestic demand and the huge depreciation of Korean won associated with the crisis.

// Table 1 here//

Consistent with the high export dependency of the economy, the share of exports in shipments at plant level is quite high in Korea. During the sample period, the unweighted mean export share is between 43.6 and 54.8. The mean export share steadily declines from 1990 to 1996, but rises with the onset of the crisis. The mean export share weighted by shipment is generally lower than unweighted mean export share, suggesting that smaller exporting plants have higher export share.

It is a well-established fact that exporters are better than non-exporters by various performance standards. As a point of departure, we examine whether the same pattern holds in our data set for the period covered in this study. <Table 2> compares various plant attributes between exporters and non-exporters for three selected years. In terms of number of workers and shipments, exporters are on average much larger in size than non-exporters. The differential in shipment is more substantial than the differential in number of workers. So, the average labor productivity of exporters, measured by production and value added per worker, are higher than that of non-exporters. Compared with the value added per worker differential, the differential in production per worker between exporters and non-exporters are more pronounced. This might reflect more intermediate-intensive production structure of exporters relative to non-exporters. Although exporters have higher capital-labor ratio and higher share of non-production workers in employment than non-exporters, these differences in inputs do not fully account for the differences in labor productivity. As a consequence, total factor productivity levels of exporting plants are, on average, higher than those plants producing for domestic market only. Some of the differences in the total factor productivity levels may be attributed to the differences in R&D intensity. Controlling for the size of shipments, exporters spent about twice as much on R&D as non-exporters. From the worker's point of view, exporters had more desirable attributes than non-exporters. Average wage of exporters is higher than that of non-exporters. Although both production worker's wage and non-production worker's wage are higher in exporters than in non-exporters, the differential in non-production worker's wage is more pronounced.

// Table 2 here//

III. Empirical Strategy: Propensity Score Matching

It is now well-recognized in the literature that the decision to become an exporter is not a random event but the result of deliberate choice calling for extra efforts to correctly identify the true effect of becoming an exporter on its productivity(Loecker(2007), Albornoz and Ercolani(2007)). The participation decision in export market is likely to be correlated with the stochastic disturbance terms in data generating process for firm's productivity so that the traditional simple mean difference test on productivity differences between exporters and non-exporters does not provide a correct answer. Matching method has been gaining popularity among applied researchers regarded as a promising analytical tool with which we can cope with statistical problems stemming from endogenous participation decision.

The underlying motivation for the matching method is to reproduce the treatment group (exporters) among the non-treated (non-exporters) so that we can reproduce the experiment conditions in a non-experimental setting. The matching method construct a version of sample analog of the missing information on the treated outcomes had they not been treated by paring each participants with members of the non-treated group. The crucial assumption in matching method is that conditional on some observable characteristics of the participants, the potential outcome in the absence of the treatment is independent of the participation status.

$$y_i^0 \perp d_i \,|X_i \qquad (2)$$

where y_i^0 is the potential outcome in the absence of the treatment, d_i is the dummy to indicate participation, and X_i is the vector of conditional variables. The basic idea of the matching method is to construct a sample analog of counterfactual control group from the members of non-participating group that possess conditioning variables as close to those of treatment group as possible. In practice, it is very difficult to construct a control group that can satisfy the condition in (2) especially when the dimension of the conditioning vector X_i is high.

Rosenbaum and Rubin(1983) propose a smart way to overcome the curse of dimensionality in traditional matching method. Suppose that the conditional probability of firm *i*'s becoming an exporter propensity score can be specified as a function of observable characteristics of the firm before the participation;

$$p(X_i) = \Pr[d_i = 1 | X_i] = E(d_i | X_i) \tag{3}$$

Rosenbaum and Rubin(1983) call the probability function in (3) propensity score and show that if the conditional independence assumption in (2) is satisfied it is also valid for $p(X_i)$ that

$$y_i^0 \perp d_i \,|\, p(X_i) \tag{4}$$

We have replaced the multi-dimensional vector with one-dimensional variable with the same information contents that highly complicated matching problem in (2) is reduced to a simple single dimensional problem in (4).

One can define the average treatment effect on the treated (ATT) as;

$$\begin{aligned} ATT &= E\left[y_i^1 - y_i^0 | d_i = 1\right] = E\left[E\left[y_i^1 - y_i^0 | d_i = 1, p(X_i)\right]\right] \\ &= E\left[E\left[y_i^1 | d_i = 1, p(X_i)\right] - E\left[y_i^0 | d_i = 1, p(X_i)\right]\right] \end{aligned} \tag{5}$$

where y_i^0 is the potential outcome that would have been observable had participating firm i decided not to start exporting and y_i^1 is the observable outcome for participating firm i. Note that ATT is not the measure for the effect of exporting on all firms but on firms that start to export.

Since y_i^0 is not observable, the definition (5) is not operational. Given that the unconfoundedness condition under propensity score (4) satisfied and the propensity score (3) known, the following definition is equivalent to (5).

$$ATT = E\lfloor y_i^1 - y_i^0 | d_i = 1 \rfloor = E\lfloor E\lfloor y_i^1 | d_i = 1, p(X_i) \rfloor - E\lfloor y_i^0 | d_i = 0, p(X_i) \rfloor \rfloor \qquad (6)$$

Both y_i^0 and y_i^1 are observable in (6), one can construct an estimator for ATT through a version of sample analog.

As the first step toward estimating ATT, we estimate the probability function in (3) with the following probit specification.

$$p(X_i : \beta, \sigma) = 1 - \int_{-\infty}^{\beta' X_i} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) dz \qquad (7)$$

Log of total factor productivity, log of the number of workers employed, log of capital per worker, 9 yearly dummies, and 10 industry dummies are included in the conditioning vector X_i. As for conditioning variables, we use the values from one year before the firm starts to export in order to account for time difference in decision and actual participation,

Based on estimated version of (7), one can calculate propensity score for all observations, participant or non-participants. Let T be the set of treated (participating) units and C the set of control units, respectively and denote by $C(i)$ the set of control units matched to the treated unit i with an estimated value of propensity score of p_i. Then, we pick the set of nearest-neighbor matching as;

$$C(i) = \min_j \| p_i - p_j \| \tag{8}$$

Denote the number of controls matched with a treated unit $i \in T$ by N_i^C and define the weight $w_{ij} = \frac{1}{N_i^C}$ if $j \in C(i)$ and $w_{ij} = 0$ otherwise. Then, the propensity score matching estimator for the average treatment effect on the treated at time *t* is given by;

$$ATT_t^* = \frac{1}{N^T} \sum_{i \in T} \left(y_{i,t}^1 - \sum_{j \in C(i)} w_{ij} y_{j,t}^0 \right) \tag{9}$$

where $y_{i,t}^1$ is the observed value on firm *i* in the treatment group at time *t* and $y_{j,t}^0$ is the observed value on firm *j* in the matched control group for firm *i* at time *t*.

Moreover, one can easily show that the variance of the estimator in (9) is given by;

$$Var(ATT_t^*) = \frac{1}{N^T} Var(y_{i,t}^1) + \frac{1}{(N^T)^2} \sum_{i \in T} \sum_{j \in C(i)} (w_{ij})^2 Var(y_{j,t}^0) \tag{10}$$

One can estimate asymptotically consistent estimator for (10) by replacing two variances with corresponding sample analogs.

We use two different versions of propensity score matching procedure written in STATA language; **attn.ado** explained in Becker and Ichino(2002) and **psmatch2.ado** provided by Leuven and Sianesi(2008). The two procedures follow identical approach in estimating propensity score and constructing the control group except for the fact that the former tries to verify the unconfoundedness condition in the sample by dividing the entire region of estimated propensity scores into several blocks and construct the matched control group within the block to which the treated observation belongs.

In order to detect the possibility that the channel of learning by export works in different intensity depending on firm characteristics and industry, we divide the entire sample into several categories according to firm characteristics such as export ratio, skill intensity, firm size measured by the number of workers, and R&D intensity as well as industry and measure the average treatment effect of the treated for each sub-sample.

IV. Main Empirical Results: Learning-By-Exporting Effects

IV. 1 Results at Manufacturing Level

Table 3 shows our main results at manufacturing level. The estimated coefficients denote percentage productivity differential between plants that start exporting and their domestic counterparts s years after entering the export market. We report results from the two versions of propensity score matching procedure.

// Table 3 here//

Overall, all coefficients are positive and highly significant, suggesting the existence of learning-by-exporting effect. Exporting plants become more productive than those that produce for domestic market only immediately after entering the export market and the gap widens further although at a decelerating pace. Furthermore, results from the two matching techniques are quite similar not only qualitatively but also qualitatively. The estimated coefficients from **attn.ado** procedure indicate that starters become about 4.1 percent more productive in the year of entry. In the following years, starters become and remain between 6.4 and 7.7 percent more productive. Thus, it is suggested that entering the export market has a permanent effect on productivity level, especially during the first several years after entry. In other words, export market entry has a temporary effect on productivity growth especially during the first several years after entry.

IV. 2 Sub-Group Estimation: Plant Characteristics

Next, we divided our sample into three sub-groups according to various plant characteristics, such as exports-production ratio, skill intensity, plant size (proxied by number of workers), and R&D-production ratio. Then we estimated the learning-by-exporting effect separately for each sub-group. Table 4 shows, firstly, that the estimated coefficients are generally larger and more significant for plants with higher exports-production ratio. For group I (exports-production ratio less than 10%), starters become between 2.5 and 4.1 percent more productive after one year of exporting experience (s>= 1), based on **attn.ado** procedure.[5] For group III (exports-production ratio greater than 50%), starters become and remain between 9.5 and 11.4 percent more productive during the same period. We discussed earlier that if the estimated learning-by-exporting effect indeed captures the learning associated with exporting activity then the effect is likely to be stronger for plants with higher exports-output ratio; if learning-by-exporting arises from contact with foreign buyers and foreign market, which requires costly resources, then firms with exporting as their major activity are likely to be more heavily exposed to foreign contact. The above results are pretty much consistent with our expectation.

// Table 4 here//

Secondly, the estimated learning-by-doing effect is more pronounced for plants with higher skill intensity[6]. For group I (skill intensity less than 10%), starters become between 1.5 and 2.6 percent more productive after one year of exporting experience (s>= 1), based on **attn.ado** procedure. For group III (skill intensity greater than 40%), starters become and remain between 9.5 and 11.4 percent more productive during the same period. These results suggest that domestic "absorptive capacity" matters for exporting plants to receive international knowledge spillovers. Specifically, these results are consistent with the previous empirical literature that emphasizes the role of human

[5] Estimation results based on psmatch2.ado procedure are reported in appendix tables.
[6] Skill intensity is measured by the share of non-production worker in sum of

capital in facilitating technology adoption (Welch 1975, Bartel and Lichtenberg 1987, Foster and Rosenzweig 1995, Benhabib and Spiegel 1994)[7].

Thirdly, we also examined whether the degree of learning-by-exporting is related to plant size, by diving our sample into three groups: group I (number of workers 5-10), group II (11-49), and group III (50+). Table 4 suggests that the estimated learning-by-exporting effect is generally larger and more significant for smaller plants. As argued by Albornoz and Ercolani (2007), there seems to be no a priori reason to expect larger learning-by-exporting effects for small exporters.[8] On one hand, large firms are generally more structured and this would facilitate a better absorption and use of new knowledge. On the other hand, knowledge might be easier to disseminate in a small firm. The results seem to suggest that the latter effect dominates.

Finally, we examine whether plants with higher R&D investment exhibit larger learning-by-exporting effect. To do so, we classified plants into four sub-groups: group I (no R&D), group II (R&D expenditure/production less than 2%), group III (2 to 10%), group IV (10%+). Somewhat surprisingly, learning-by-exporting effect was significantly estimated only in group I. Although we don't have a clear interpretation of these results, we conjecture that R&D-production ratio reflects industry specific characteristics, rather than innovativeness of firms.[9]

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production and non-production worker.

[7] These studies are empirical investigations of Nelson-Phelps hypothesis which suggests that the rate at which the gap between the technology frontier and the current level of productivity is closed depends on the level of human capital. See Benhabib and Spiegel (2005) for detailed explanation.

[8] They also find that small firms learn more from exporting activities using firm-level panel data on Argentinian manufacturing.

[9] It is a well known fact that R&D intensity varies a lot across industries. *To be added.

IV. 3 Results at Disaggregated Industries

In order to examine whether there are differences in the estimated productivity gains, we divided our sample into 10 sub-industries and repeated our estimation procedure for each industry. Table 5 shows that the learning-by-exporting effect is visible in textile and apparel, chemical, metal, transport equipment, while it is not significantly estimated in food, wood and pulp, general machinery, electronics, precision instrument. Roughly speaking, the former industries tend to be Korea's export industries. It is somewhat surprising to find no significant learning-by-exporting effect in electronics industry. (to be added)

// Table 5 here//

IV. 4 Learning-by-Exporting and Export Destination of Industries

(to be added)

V. Concluding Remarks

(to be added)

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(to be added)

<Table 1>. Number of Exporters and Export Intensity

Year	Total number of plants (percent)	non-exporters (percent)	Exporters (percent)	exports/shipments ratio (percent)	
				unweighted	weighted
1990	68,690 (100)	58,392 (85.0)	10,298 (15.0)	54.8	37.3
1991	72,213 (100)	61,189 (84.7)	11,024 (15.3)	54.3	37.3
1992	74,679 (100)	63,241 (84.7)	11,438 (15.3)	51.7	36.3
1993	88,864 (100)	77,514 (87.2)	11,350 (12.8)	49.9	36.0
1994	91,372 (100)	80,319 (87.9)	11,053 (12.1)	47.2	35.9
1995	96,202 (100)	85,138 (88.5)	11,064 (11.5)	44.8	37.2
1996	97,141 (100)	86,502 (89.0)	10,639 (11.0)	43.6	35.3
1997	92,138 (100)	80,963 (87.9)	11,175 (12.1)	44.2	38.0
1998	79,544 (100)	67,767 (85.2)	11,777 (14.8)	44.7	48.7

Source: Table 1 from Hahn (2004)

<Table 2>. Performance Characteristics of Exporters vs. Non-exporters

	1990		1994		1998	
	exporters	non-exporters	exporters	non-exporters	exporters	non-exporters
Employment (person)	153.6	24.5	119.4	20.0	95.1	17.8
Shipments (million won)	11,505.5	957.0	17,637.1	1,260.3	25,896.8	1,773.8
production per worker (million won)	50.5	26.8	92.4	47.0	155.0	74.2
value-added per worker (million won)	16.5	11.3	31.0	20.4	51.3	29.6
TFP	0.005	−0.046	0.183	0.138	0.329	0.209
capital per worker (million won)	16.8	11.9	36.0	21.9	64.6	36.7
non-production worker/ total employment (percent)	24.9	17.1	27.5	17.5	29.6	19.2
average wage (million won)	5.7	5.1	10.3	9.2	13.7	11.5
average production wage (million won)	5.5	5.1	10.0	9.2	13.1	11.4
average non-production wage (million won)	6.8	5.3	11.6	9.4	15.6	12.4
R&D/shipments (percent)	–	–	1.2	0.6	1.4	0.6

Source: Table 2 from Hahn (2004)

<Table 3> Average Productivity Gain of Exporters

Matching Method		s = 0	s = 1	s = 2	s = 3
ATTN	ATT	0.041*** (0.008)	0.065*** (0.010)	0.077*** (0.011)	0.064*** (0.014)
	No. Treated	5696	5696	5696	5696
	No. Controls	3725	2206	1401	854
PSMATCH2	ATT	0.030*** (0.008)	0.051*** (0.011)	0.056*** (0.014)	0.058*** (0.019)
	No. Treated	5650	2492	1354	743
	No. Controls	76576	54362	38237	27244

<Table 4>　Average Productivity Gain of Exporters by Firm Characteristics I : ATTN

Firm Characteristics			s = 0	s = 1	s = 2	s = 3
Export Ratio	Low	ATT	0.043***	0.041***	0.025	0.04**
			(0.013)	(0.015)	(0.018)	(0.020)
		No. Treated	2141	2141	2141	2141
		No. Controls	1457	834	546	352
	Medium	ATT	0.014	0.066***	0.081***	0.071***
			(0.013)	(0.015)	(0.017)	(0.021)
		No. Treated	1840	1840	1840	1840
		No. Controls	1338	755	474	288
	High	ATT	0.06***	0.112***	0.114***	0.095***
			(0.014)	(0.016)	(0.019)	(0.021)
		No. Treated	1696	1696	1696	1696
		No. Controls	1230	744	481	325
Skill Intensity	Low	ATT	0.009	0.021	0.015	0.026
			(0.020)	(0.027)	(0.033)	(0.046)
		No. Treated	1100	1100	1100	1100
		No. Controls	552	314	185	100
	Medium	ATT	0.026***	0.054***	0.065***	0.033**
			(0.009)	(0.010)	(0.012)	(0.014)
		No. Treated	3329	3329	3329	3329
		No. Controls	2737	1590	1031	652
	High	ATT	0.049***	0.065***	0.068***	0.072***
			(0.017)	(0.022)	(0.024)	(0.027)
		No. Treated	1267	1267	1267	1267
		No. Controls	964	511	316	205
Number Of workers	Low	ATT	0.078***	0.124***	0.207***	0.177***
			(0.015)	(0.020)	(0.027)	(0.033)
		No. Treated	1456	1456	1456	1456
		No. Controls	811	381	201	106
	Medium	ATT	0.028***	0.055***	0.058***	0.049***
			(0.010)	(0.011)	(0.013)	(0.016)
		No. Treated	3183	3183	3183	3183
		No. Controls	2667	1523	997	607
	High	ATT	0.003	-0.056***	-0.009	0.033
			(0.020)	(0.023)	(0.027)	(0.028)
		No. Treated	1057	1057	1057	1057
		No. Controls	675	508	361	248
R&D	None	ATT	0.051***	0.065***	0.08***	0.069***
			(0.009)	(0.010)	(0.012)	(0.014)
		No. Treated	4723	4723	4723	4723
		No. Controls	3130	1866	1225	797
	Low	ATT	-0.009	0.037	0.065	0.07
			(0.035)	(0.036)	(0.042)	(0.044)
		No. Treated	352	352	352	352
		No. Controls	216	132	87	56
	Medium	ATT	-0.016	0.016	0.022	0.041
			(0.031)	(0.038)	(0.046)	(0.041)
		No. Treated	446	446	446	446
		No. Controls	270	157	91	61
	High	ATT	0.03	-0.034	-0.033	0.07
			(0.048)	(0.061)	(0.077)	(0.073)
		No. Treated	175	175	175	175
		No. Controls	113	62	43	27

<Table 5> Average Productivity Gain of Exporters by Industry I; ATTN

		t=0	t=1	t=2	t=3
Food	ATT	0.048 (0.038)	0.01 (0.042)	-0.028 (0.052)	-0.006 (0.058)
	No. Treated	278	278	278	278
	No. Controls	194	100	66	51
Textile and Apparel	ATT	0.099*** (0.018)	0.117*** (0.019)	0.129*** (0.021)	0.097*** (0.025)
	No. Treated	1331	1331	1331	1331
	No. Controls	894	552	355	223
Wood and Pulp	ATT	-0.015 (0.033)	-0.016 (0.039)	-0.043 (0.042)	-0.138*** (0.054)
	No. Treated	243	243	243	243
	No. Controls	177	115	77	52
Chemical	ATT	0.026 (0.021)	0.041 (0.028)	0.063* (0.033)	0.158*** (0.035)
	No. Treated	696	696	696	696
	No. Controls	444	255	163	109
Metal	ATT	0.09*** (0.029)	0.09** (0.038)	0.067 (0.044)	0.013 (0.045)
	No. Treated	319	319	319	319
	No. Controls	215	128	74	49
General Machinery	ATT	0.019 (0.015)	0.005 (0.019)	-0.013 (0.024)	-0.002 (0.026)
	No. Treated	1436	1436	1436	1436
	No. Controls	936	528	332	193
Electronics	ATT	-0.003 (0.026)	-0.016 (0.031)	-0.045 (0.033)	-0.024 (0.033)
	No. Treated	618	618	618	618
	No. Controls	401	235	157	109
Precision Instrument	ATT	-0.016 (0.048)	-0.022 (0.056)	0.004 (0.054)	-0.001 (0.074)
	No. Treated	207	207	207	207
	No. Controls	122	76	44	27
Transport Equipment	ATT	0.018 (0.040)	0.039 (0.045)	0.111** (0.052)	0.15*** (0.051)
	No. Treated	246	246	246	246
	No. Controls	176	114	77	52
Other	ATT	0.043 (0.029)	0.071* (0.040)	0.1** (0.050)	0.183*** (0.055)
	No. Treated	322	322	322	322
	No. Controls	212	112	70	44

<Table A.1> Average Productivity Gain of Exporters by Firm Characteristics II : PSMATCH2

			t=0	t=1	t=2	T=3
Export Ratio	Low	ATT	0.036***	0.001	0.021	-0.005
			(0.011)	(0.016)	(0.022)	(0.026)
		No. Treated	2129	972	526	304
		No. Controls	76576	54362	38237	27244
	Medium	ATT	0.019	0.071***	0.052**	0.054
			(0.012)	(0.018)	(0.024)	(0.033)
		No. Treated	1835	769	424	222
		No. Controls	76576	54362	38237	27244
	High	ATT	0.054***	0.109***	0.105***	0.074**
			(0.013)	(0.019)	(0.025)	(0.035)
		No. Treated	1686	747	402	216
		No. Controls	76576	54362	38237	27244
Skill Intensity	Low	ATT	-0.014	0.004	0.086**	0.099**
			(0.016)	(0.026)	(0.037)	(0.050)
		No. Treated	1086	406	191	90
		No. Controls	30592	20469	13645	8953
	Medium	ATT	0.026***	0.046***	0.043***	0.025
			(0.009)	(0.013)	(0.017)	(0.025)
		No. Treated	3306	1517	844	472
		No. Controls	37772	27997	20343	14916
	High	ATT	0.062***	0.057**	0.063**	0.104***
			(0.017)	(0.025)	(0.033)	(0.041)
		No. Treated	1258	569	319	181
		No. Controls	8212	5896	4249	3120
Number Of Workers	Low	ATT	0.056***	0.074***	0.108***	0.082
			(0.015)	(0.026)	(0.042)	(0.060)
		No. Treated	1443	423	153	68
		No. Controls	39564	25645	16386	10862
	Medium	ATT	0.057***	0.059***	0.069***	0.084***
			(0.010)	(0.014)	(0.018)	(0.024)
		No. Treated	3161	1407	764	411
		No. Controls	33433	25722	19349	14321
	High	ATT	0.031	-0.023	-0.036	0.035
			(0.019)	(0.024)	(0.030)	(0.040)
		No. Treated	1046	662	437	264
		No. Controls	3579	2995	2502	2061
R&D	None	ATT	0.033***	0.041***	0.055***	0.039*
			(0.008)	(0.012)	(0.015)	(0.022)
		No. Treated	4678	2040	1080	598
		No. Controls	73923	52426	36829	26816
	Low	ATT	0.005	-0.008	0.000	0.066
			(0.035)	(0.041)	(0.049)	(0.066)
		No. Treated	351	188	122	66
		No. Controls	825	605	455	302
	Medium	ATT	-0.007	0.031	-0.024	0.055
			(0.030)	(0.038)	(0.056)	(0.068)
		No. Treated	446	199	114	61
		No. Controls	1201	881	637	453
	High	ATT	0.049	-0.014	-0.029	0.089
			(0.047)	(0.062)	(0.086)	(0.132)
		No. Treated	175	65	38	18
		No. Controls	627	424	298	180

<Table A. 2> Average Productivity Gain of Exporters by Industry II; PSMATCH2

		t=0	t=1	t=2	t=3
Food	ATT	0.074** (0.036)	0.077 (0.052)	0.031 (0.063)	0.100 (0.064)
	No. Treated	273	132	90	58
	No. Controls	4868	3837	2939	2224
Textile and Apparel	ATT	0.118*** (0.016)	0.128*** (0.024)	0.145*** (0.030)	0.113*** (0.042)
	No. Treated	1316	561	293	150
	No. Controls	17415	11983	8374	5743
Wood and Pulp	ATT	0.033 (0.036)	0.029 (0.051)	0.009 (0.059)	0.003 (0.097)
	No. Treated	240	102	56	22
	No. Controls	8888	6466	4726	3557
Chemical	ATT	0.038** (0.019)	0.031 (0.030)	0.086** (0.037)	0.091* (0.047)
	No. Treated	695	332	181	102
	No. Controls	6188	4462	3198	2329
Metal	ATT	0.052* (0.027)	0.046 (0.040)	0.123** (0.054)	0.044 (0.064)
	No. Treated	313	138	73	42
	No. Controls	5707	4346	3287	2554
General Machinery	ATT	0.015 (0.014)	0.016 (0.022)	-0.020 (0.034)	-0.017 (0.043)
	No. Treated	1427	604	325	170
	No. Controls	18280	12732	8572	5895
Electronics	ATT	0.002 (0.023)	0.020 (0.033)	0.010 (0.042)	-0.026 (0.048)
	No. Treated	615	268	148	89
	No. Controls	5541	3837	2639	1815
Precision Instrument	ATT	0.028 (0.043)	0.009 (0.062)	0.087 (0.078)	0.139 (0.091)
	No. Treated	207	93	50	32
	No. Controls	1225	820	560	368
Transport Equipment	ATT	-0.019 (0.038)	0.010 (0.048)	0.016 (0.075)	0.124* (0.075)
	No. Treated	245	120	68	37
	No. Controls	3473	2465	1705	1251
Other	ATT	0.043 (0.028)	0.043 (0.040)	0.108** (0.051)	0.101 (0.087)
	No. Treated	319	142	70	41
	No. Controls	4991	3414	2237	1508